



Classification of Cancer Cells and Dental Caries Detection using Deep Learning Algorithms

Sunkara.Naga Sindhu¹ | Dr Raavi. Satya Prasad²

¹Research Scholar, Acharya Nagarjuna University, Guntur, AP, India. sunkaranagasindhu9@gmail.com

¹Assistant Professor, Department of Computer Science & Engineering, Dhanekula Institute of Engineering & Technology, Ganguru, Vijayawada, A.P., India, snsindhu@diet.ac.in ; orcid : 0009-0000-5621-0363

²Professor and Dean R & D, Department of Computer Science & Engineering, Dhanekula Institute of Engineering & Technology, Ganguru, Vijayawada, A.P., India, deanresearch@diet.ac.in; orcid: 0009-0007-1894-2417

To Cite this Article

Sunkara.Naga Sindhu and Dr Raavi. Satya Prasad, Classification of Cancer Cells and Dental Caries Detection using Deep Learning Algorithms, International Journal for Modern Trends in Science and Technology, 2024, 10(11), pages. 07-13. <https://doi.org/10.46501/IJMTST1011002>

Article Info

Received: 17 October 2024; Accepted: 15 November 2024.; Published: 18 November 2024.

Copyright © Sunkara.Naga Sindhu et al; This is an open access article distributed under the [Creative Commons Attribution License](#), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

ABSTRACT

Detecting cancer cells, particularly within dental cavities, is not typical, as dental cavities are mainly connected with tooth decay caused by bacterial activity. However, cancers of the oral cavity, such as oral squamous cell carcinoma, can sometimes be found in the mouth, including on the gums, tongue, and other tissues. Dentists often thoroughly examine the oral cavity to look for abnormal areas. A biopsy may be performed to determine if cancer cells are present if a suspicious lesion is found. This process, while effective, can be time-consuming. In this paper, an Automated Deep Model (ADM) is developed to detect and classify cancer cells and teeth caries based on the regions affected, potentially speeding up the detection and diagnosis process. The proposed approach works for both cancer and dental caries detection, involving steps like training, preprocessing, and segmentation to improve model performance. Deep learning algorithms have been increasingly applied to classify cancer cells and detect dental caries in the mouth. The proposed approach combines pre-trained RESNET50 with transfer learning and classification model Support Vector Machines (SVMs) with Deep Features. The segmentation model Fully Convolutional Networks (FCNs) is used for pixel-wise segmentation of dental images to identify dental caries and abnormal cancer cells. The performance of the proposed approach shows a massive detection and classification rate compared with existing models.

KEYWORDS: Dental Cavities, Cancer Cells, Automated Deep Model (ADM), RESNET50, Transfer Learning, Support Vector Machines (SVMs), and Fully Convolutional Networks (FCNs).

1. Introduction

The classification of cancer cells and the detection of dental caries are two crucial areas in medical diagnostics that have gained significant attention with the advent of deep-learning technologies. Both tasks traditionally rely on expert diagnosis through visual inspection, imaging techniques, and laboratory analysis, which can be time-consuming and prone to human error. Deep learning (DL), a subset of machine learning based on artificial neural networks, has emerged as a powerful tool to enhance the accuracy and efficiency of these medical diagnoses. Cancer, characterized by the abnormal growth of cells, is a leading cause of death globally. The early and accurate classification of cancer cells is essential for effective treatment planning and improving patient outcomes. Pathologists use traditional methods like biopsy analysis and imaging modalities (MRI, CT scans, and histopathological slides) to identify cancer cells. However, these processes can be subject to limitations such as inter-observer variability, delayed diagnoses, and diagnostic inaccuracies. Dental caries, commonly known as tooth decay or cavities, are among the most prevalent oral diseases globally. It occurs due to the demineralization of tooth enamel by acids produced by bacteria. Early detection of dental caries is vital to prevent tooth decay progression, which can lead to tooth loss and other serious complications. Traditional methods for caries detection include visual-tactile examination, radiographs, and fluorescence-based techniques, but these methods may only sometimes detect caries at early stages.

DL algorithms, particularly convolutional neural networks (CNNs), have revolutionized cancer diagnosis by automatically learning patterns from large datasets of medical images. These algorithms are trained to detect cancerous tissues or cells in images with high accuracy and minimal human intervention. By analyzing microscopic images of tissues (histopathology images) or radiological scans, DL models can distinguish between cancerous and non-cancerous cells and even classify cancer types and stages. Techniques such as transfer learning, where pre-trained models are fine-tuned on medical data, and attention mechanisms further improve the model's ability to focus on relevant features. The use of DL algorithms for cancer cell classification and dental caries detection represents a broader trend of incorporating artificial intelligence (AI) into healthcare

systems. DL models offer numerous advantages, such as increased speed, reproducibility, and the ability to analyze large amounts of data. However, challenges remain, including the need for high-quality annotated datasets, regulatory approvals, and addressing concerns related to model interpretability and transparency.

2. Literature Survey

Lam DW et al. [13] compared the biomimetic morphology of single-molar dental prostheses designed by an AI system and by a trained dental technician using commercial dental CAD software programs. Lee et al. [14] evaluated the efficacy of deep CNN algorithms for detection and diagnosis of dental caries on periapical radiographs. The diagnostic accuracies of premolar, molar, and both premolar and molar models were 89.0% (80.4-93.3), 88.0% (79.2-93.1), and 82.0% (75.5-87.1), respectively. The deep CNN algorithm achieved an AUC of 0.917 (95% CI 0.860-0.975) on premolar, an AUC of 0.890 (95% CI 0.819-0.961) on molar, and an AUC of 0.845 (95% CI 0.790-0.901) on both premolar and molar models. The premolar model provided the best AUC, which was significantly greater than those for other models ($P < 0.001$). Gao et al. [15] proposed a mutually supervised few-shot segmentation network. First, the feature maps from intermediate convolution layers are fused to enrich the capacity of feature representation. Second, the support image and query image are combined into a bipartite graph, and the graph attention network is adopted to avoid losing spatial information and increase the number of pixels in the support image to guide the query image segmentation. Third, the attention map of the query image is used as prior information to enhance the support image segmentation, which forms a mutually supervised regime. Finally, the attention maps of the intermediate layers are fused and sent into the graph reasoning layer to infer the pixel categories. Experiments are conducted on the PASCAL VOC- 5i dataset and FSS-1000 dataset, and the results demonstrate the effectiveness and superior performance of our method compared with other baseline methods. \ Sindhu et al. [16] proposed an automated approach for dental cavities detection utilizing a Neural Turing Machines (NTM) and High Intensity Color Detection (NTM-HICD) model. These two models process the input samples in a sequence order. NTM is a type of artificial neural network (ANN) architecture that

combines neural networks with external memory structures. NTM mainly designed to mimic the ability of a Turing machine to read the interesting patterns from various disease detection. The proposed NTM-HICD system combines the strengths of multiple deep learning algorithms to enhance the accuracy and robustness of dental cavity detection. The design incorporates three primary components: image processing, feature extraction, and classification. Firstly, dental X-rays are processed to enhance the quality of input data. A pre-trained model DeepLabV3+ is used to train on dental dataset. The images are then subjected to effected region extraction to focus on the tooth areas for more targeted analysis. Secondly, a set of diverse feature extraction techniques is applied to capture comprehensive information from the effected regions. Imak et al. [17] proposed a novel approach for the automatic diagnosis of dental caries based on periapical images. The proposed procedure used a multi-input deep convolutional neural network ensemble (MI-DCNNE) model. Specifically, a score-based ensemble scheme was employed to increase the achievement of the proposed MI-DCNNE method. The inputs to the proposed approach were both raw periapical images and an enhanced form of it. The score fusion was carried out in the Softmax layer of the proposed multi-input CNN architecture. In the experimental works, a periapical image dataset (340 images) covering both caries and non-caries images were used for the performance evaluation of the proposed method. According to the results, it was seen that the proposed model is quite successful in the diagnosis of dental caries. The reported accuracy score is 99.13%. This result shows that the proposed MI-DCNNE model can effectively contribute to the classification of dental caries. Singh et al. [18] proposed an automated caries detection system based on Radon Transformation (RT) and Discrete Cosine Transformation (DCT). The Radon Transformation (RT) is performed on these X-Ray images for each degree to capture the low frequency details. Then 2-D DCT is applied to RT images to obtain the frequency features (DCT coefficients). These features are further converted to 1-D coefficient vector in Zigzag fashion which is subjected to Principal Component Analysis (PCA) for feature extraction.

3. Pre-Trained RESNET50 (training on cancer cells and dental cavities)

Using a pre-trained ResNet-50 model for tasks such as mouth cancer cell detection and dental cavity detection can leverage transfer learning to improve performance and reduce the need for large amounts of labeled data. ResNet50, or Residual Networks with 50 layers, is a pre-trained model that has been trained on a large dataset, such as ImageNet, to recognize a wide variety of objects. This pre-training allows the model to learn general image features, which can be fine-tuned for specific tasks like the detection of mouth cancer cells or dental cavities. ResNet50 employs a residual learning framework that helps mitigate the degradation problem, where increasing depth in CNNs can degrade the performance due to vanishing gradients. The core idea is to use residual blocks that allow gradients to flow through identity mappings, thereby ensuring deeper networks can still be trained effectively. The architecture is composed of:

- 50 layers (including convolutional, pooling, and fully connected layers).
- Residual blocks, each containing identity mappings that ease gradient propagation.
- Global average pooling followed by a fully connected layer and softmax for classification.

Using a pre-trained ResNet50 model provides a major advantage: rather than training the network from scratch, transfer learning can be employed. In this approach, the network is initially trained on ImageNet, and the learned features are transferred to the new task by fine-tuning the model with specific medical images, such as those related to mouth cancer cells and dental cavities. Mouth cancer (oral squamous cell carcinoma) detection using medical imaging requires sophisticated pattern recognition techniques to identify cancerous lesions. ResNet50 can be fine-tuned on histopathological images of mouth cells to distinguish between benign and malignant lesions. The model's pre-trained convolutional layers are capable of identifying low-level features such as edges, textures, and shapes, which are important in cancer detection. The use of pre-trained ResNet50 models for mouth cancer and dental cavities detection offers a powerful tool in medical diagnostics. By employing transfer learning, the model can be fine-tuned to accurately classify cancerous cells and

detect cavities in dental images, providing valuable assistance to healthcare professionals in early disease detection and prevention.

1. Convolutional Layers

In ResNet-50, the convolutional layers are used to extract features from input images. The convolution operation is represented by:

$$Y = W * X + b$$

2. Batch Normalization

Batch normalization is used to stabilize and speed up the training process. The batch normalization equation is:

$$\hat{x} = \frac{x - \mu}{\sqrt{\sigma^2 + \epsilon}}, \text{ and } y = \gamma \hat{x} + \beta$$

3. Residual Block

The shortcut connections allow the model to skip layers and help address the vanishing gradient problem. The residual block can be represented by:

$$y = F(x, \{W_i\}) + x$$

4. Activation Function (ReLU)

The activation function commonly used in ResNet-50 is the ReLU (Rectified Linear Unit), defined as:

$$f(x) = \max(0, x)$$

5. Global Average Pooling

It typically ends with a global average pooling layer to reduce the spatial dimensions of the feature maps:

$$y = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W x_{i,j}$$

6. Fully Connected Layer (FCL)

The final FCL (which was originally used for ImageNet classification) would be modified to match the number of classes in the mouth cancer and dental cavity detection task:

$$y = Wx + b$$

7. Softmax Function (for classification)

In this classification task, a softmax function is applied to the output of the fully connected layer:

$$P(y = c/x) = \frac{e^{z_c}}{\sum_{j=1}^C e^{z_j}}$$

Last fully connected layer would have a different number of outputs depending on whether the classification task is binary (cancerous vs non-cancerous or cavity vs healthy) or multi-class (specific types of cancer or stages).

Class-specific loss for tasks related to mouth cancer and dental cavities will be used to optimize the model in such cases.

Transfer Learning

Transfer learning, a technique that leverages pre-trained models on large datasets and fine-tunes them for specific tasks, has emerged as a powerful tool to address this limitation. Among the prominent pre-trained models, ResNet50, a deep convolutional neural network (CNN) known for its success in image recognition tasks, has gained popularity for its effectiveness in medical applications, including cancer cell and dental cavity detection [19]. Transfer learning refers to the process of taking a model trained on one task and applying its learned features to a new, yet related task. This is particularly beneficial in medical imaging, where datasets may be small and difficult to obtain, yet the task often involves similar low-level image features like edges, textures, and patterns. ResNet50, trained on large image datasets like ImageNet, has already learned to capture intricate image features that can be transferred to medical imaging domains, including the detection of cancer cells and dental cavities. Detecting cancer cells through histopathological or other medical imaging methods is a challenging task due to the complexity of cellular structures and the variability in appearance across different types of cancers. Using ResNet50 as a base model for transfer learning, it is possible to fine-tune the network on cancer-specific datasets to accurately detect malignancies. The model, when trained on relevant data, can identify critical patterns and morphological features that differentiate healthy from cancerous cells.

Similar to cancer cell detection, dental cavity detection involves identifying structural anomalies in dental X-rays or intraoral images. Dental cavities appear as darkened regions where tooth decay has occurred, and detecting these features with deep learning algorithms can assist dentists in diagnosing early-stage cavities. ResNet50, fine-tuned on dental datasets, can learn to recognize subtle changes in tooth structure, improving the accuracy and speed of diagnosis.

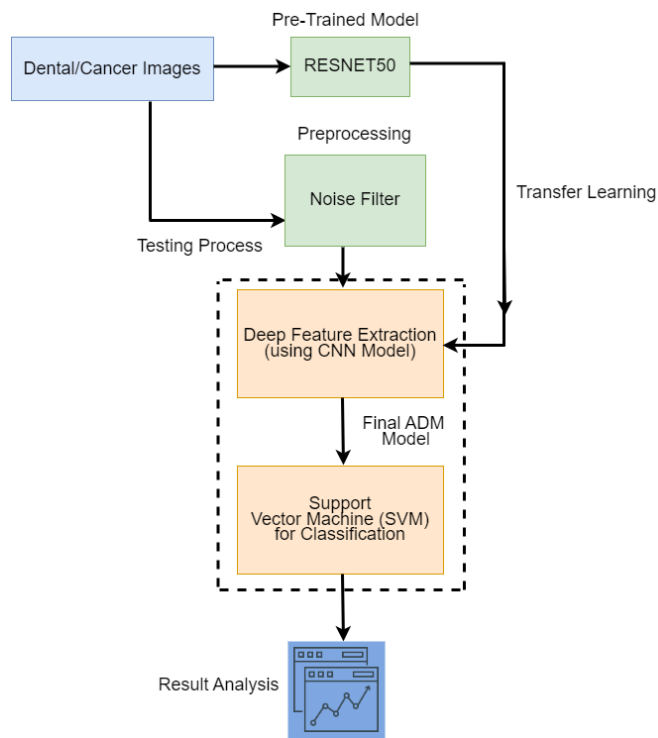


Figure 1: Overall System Architecture

4. Automated Deep Model (ADM) for Cancer Cell and Dental Cavity Detection and Classification

Cancer cell detection and dental cavity identification are crucial areas of medical and dental diagnostics, respectively, where timely and accurate detection can have significant implications for patient outcomes. The complexity and variability inherent in medical imaging, combined with the need for precision, have driven the development of automated techniques that utilize advanced machine learning and deep learning models. In this context, the Automated Deep Model (ADM), which integrates Support Vector Machines (SVM) with deep feature extraction, represents a promising approach for the detection and classification of cancer cells and dental cavities. Early detection of cancer cells can significantly improve treatment outcomes by enabling interventions at an early stage when the disease is more manageable. Similarly, dental cavities, if detected early, can prevent further tooth decay and avoid more invasive treatments such as root canals or extractions. The challenge in both domains is the accurate and efficient identification of the relevant structures in medical images, which often exhibit subtle variations that can be difficult to detect with traditional methods. In this context, the Automated Deep Model (ADM) leverages the power of deep learning models, such as Convolutional Neural Networks (CNNs), to

automatically extract deep features from medical images. Deep features represent high-level abstractions, such as edges, textures, and shapes, which are crucial for distinguishing between cancerous and non-cancerous cells, as well as identifying cavities in dental images. While deep learning models excel at feature extraction, Support Vector Machines (SVMs) are particularly effective in classification tasks, especially when dealing with smaller datasets. By combining the two approaches, ADM offers the advantage of leveraging SVM's robustness in decision-making along with deep learning's superior feature extraction capabilities.

The automated deep model (ADM) steps are given below:

Step 1: Deep Feature Extraction (using CNN Model):

Let $X \in \mathbb{R}^{n \times m \times c}$ be an input image (for example, an image of a cancer cell or dental cavity), where n , m , and c represent the image height, width, and number of channels (e.g., RGB channels), respectively.

The convolution operation for each convolutional layer can be described as:

$$F^{(l)} = \sigma(W^{(l)} * X^{(l-1)} + b^{(l)})$$

After multiple layers of convolution, pooling, and activation, you obtain deep features represented by $F^{(L)}$, where L is the final layer of the deep model.

Step 2: Support Vector Machine (SVM) for Classification

Let the deep features from the last layer be denoted as $F \in \mathbb{R}^d$, is the dimensionality of the deep feature vector.

The SVM attempts to find a hyperplane that separates the classes (e.g., cancerous vs. non-cancerous, cavity vs. healthy teeth). The decision function of the SVM is given by:

$$h(f) = \text{sign}(w^T f + b)$$

The SVM solves the following optimization problem to maximize the margin between classes:

$$\min_{w, b} \frac{1}{2} \|w\|^2 \text{ subject to } y_i(w^T f_i + b) \geq 1, \forall i$$

$y_i \in \{-1, +1\}$ is the label for each feature vector f_i .

Step 3: Final ADM Model

The overall ADM model involves feeding an input image X through the deep learning network to extract the deep features f , which are then classified by the SVM. Thus, the final prediction for an input image X is:

$$h(X) = \text{sign}(w^T \cdot f(X) + b)$$

Where $f(X)$ represents the deep feature vector extracted from image X , and the SVM performs the final classification based on these features.

This hybrid approach leverages the power of deep learning for feature extraction and the robustness of SVM for classification, making it suitable for tasks such as cancer cell detection and dental cavity identification.

Dataset Description and Performance Metrics

Using a confusion matrix, this section analyzed all algorithms in two datasets, one dental cavity, and other mouth cancer cells [20]. It assesses the algorithm's strengths based on disease detection rates. The detection rate represents the difference between actual and predicted values. The exact values are analyzed using the labels found in the dataset. The algorithms evaluate the predicted values. The first dataset is classified into four classes, and the second dataset comprises the two classes. The authors of the dataset have labeled and assigned all classes.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1 - Score} = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})}$$

Table 1: Comparison between several algorithms based on classification of dental diseases for dataset1.

Algorithm	Type of Caries	Accuracy	Precision	Recall	F1-Scoe
ANN	Smooth-Surface	0.84	0.85	0.90	0.89
	Pit and fissure	0.83	0.84	0.89	0.88
	Root	0.83	0.84	0.85	0.79
	Arrested	0.84	0.85	0.85	0.86
NTM-HICD [16]	Smooth-Surface	0.93	0.92	0.94	0.94
	Pit and fissure	0.94	0.94	0.94	0.95
	Root	0.93	0.93	0.94	0.95
	Arrested	0.93	0.94	0.94	0.94
Proposed Approach	Smooth-Surface	0.98	0.97	0.97	0.98
	Pit and fissure	0.98	0.97	0.97	0.98
	Root	0.98	0.98	0.98	0.98
	Arrested	0.98	0.98	0.97	0.98

Table 2: Comparison between several algorithms based on classification of mouth cancer cells for dataset2.

	Accuracy	Precision	Recall	F1-Scoe
ANN	89.34	90.34	90.23	90.67
NTM-HICD [16]	94.56	95.67	95.45	95.12
Proposed Approach	98.34	98.45	98.67	98.41

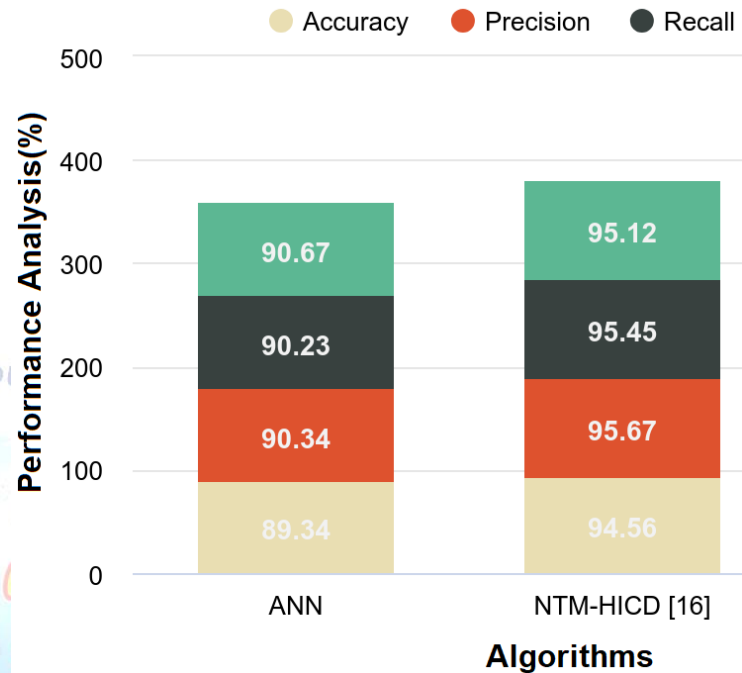


Figure 2: Comparison between several algorithms based on classification of mouth cancer cells for dataset2.

5. Conclusions

The integration of SVM with deep learning features in the Automated Deep Model (ADM) provides a powerful tool for the detection and classification of cancer cells and dental cavities. This hybrid approach combines the strengths of both techniques, resulting in a robust and efficient system that can significantly improve diagnostic accuracy and support medical professionals in delivering timely and effective care. As medical imaging technologies continue to evolve, models like ADM have the potential to further enhance early detection efforts, ultimately improving patient outcomes in both oncology and dentistry.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

- [1] J.-H. Lee, D.-H. Kim, S.-N. Jeong, and S.-H. Choi, "Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm", *J. Dent.*, Jul. 2018.
- [2] R. Esmailyfard, H. Bonyadifard, and M. Paknahad, "Dental caries detection and classification in CBCT images using deep learning", *Int. Dent. J.*, vol. 74, no. 2, pp. 328–334, Apr. 2024.
- [3] M. T. G. Thanh, N. Van Toan, V. T. N. Ngoc, N. T. Tra, C. N. Giap, and D. M. Nguyen, 'Deep learning application in dental caries detection using intraoral photos taken by smartphones', *Appl. Sci. (Basel)*, vol. 12, no. 11, p. 5504, May 2022.
- [4] Askar, H.; Krois, J.; Rohrer, C.; Mertens, S.; Elhennawy, K.; Ottolenghi, L.; Mazur, M.; Paris, S.; Schwendicke, F. Detecting white spot lesions on dental photography using deep learning: A pilot study. *J. Dent.* 2021, 107, 103615.
- [5] Mao, Q.-C.; Sun, H.-M.; Liu, Y.-B.; Jia, R.-S. Mini-YOLOv3: Real-time object detector for embedded applications. *IEEE Access* 2019, 7, 133529–133538.
- [6] Cao, C.; Wang, B.; Zhang, W.; Zeng, X.; Yan, X.; Feng, Z.; Liu, Y.; Wu, Z. An improved faster R-CNN for small object detection. *IEEE Access* 2019, 7, 106838–106846.
- [7] Thanh, M.T.G.; Van Toan, N.; Toan, D.T.T.; Thang, N.P.; Dong, N.Q.; Dung, N.T.; Hang, P.T.T.; Anh, L.Q.; Tra, N.T.; Ngoc, V.T.N. Diagnostic Value of Fluorescence Methods, Visual Inspection and Photographic Visual Examination in Initial Caries Lesion: A Systematic Review and Meta-Analysis. *Dent. J.* 2021, 9, 30.
- [8] Van Gorp G, Maes A, Lambrechts M, Jacobs R, Declerck D. Is use of CBCT without proper training justified in paediatric dental traumatology? An exploratory study. *BMC Oral Health*. 2023;23(1):270. doi: 10.1186/s12903-023-03013-y.
- [9] Park YS, Ahn JS, Kwon HB, Lee SP. Current status of dental caries diagnosis using cone beam computed tomography. *Imaging Sci Dent.* 2011;41(2):43–51. doi: 10.5624/isd.2011.41.2.43.
- [10] Al-Rawi N, Sultan A, Rajai B, Shuaeeb H, Alnajjar M, Alketbi M, et al. The effectiveness of artificial intelligence in detection of oral cancer. *Int Dent J.* 2022;72(4):436–447. doi: 10.1016/j.identj.2022.03.001.
- [11] Inês Meurer, M.; Caffery, L.J.; Bradford, N.K.; Smith, A.C. Accuracy of dental images for the diagnosis of dental caries and enamel defects in children and adolescents: A systematic review. *J. Telemed. Telecare* 2015, 21, 449–458.
- [12] Hung KF, Ai QYH, Wong LM, Yeung AWK, Li DTS, Leung YY. Current applications of deep learning and radiomics on CT and CBCT for maxillofacial diseases. *Diagnostics*. 2023;13(1):110.
- [13] Lam DW, Chau DR. Biomimetic dental prostheses designed by artificial intelligence versus CAD software. *Int Dent J.* 2023;73::S32–S33. doi: 10.1016/j.identj.2023.07.298.
- [14] Lee JH, Kim DH, Jeong SN, Choi SH. Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm. *J Dent.* 2018;77:106–111. doi: 10.1016/j.jdent.2018.07.015.
- [15] Gao H, Xiao J, Yin Y, Liu T, Shi J. A mutually supervised graph attention network for few-shot segmentation: the perspective of fully utilizing limited samples. *IEEE Trans Neural Netw Learn Syst.* 2022;1–13. doi: 10.1109/TNNLS.2022.3155486.
- [16] Sindhu, S.N., Prasad, R.S. (2024). Dental caries detection using Neural Turing Machines (NTM) and High Intensity Color Detection (NTM-HICD) model. *Revue d'Intelligence Artificielle*, Vol. 38, No. 2, pp. 671–679. <https://doi.org/10.18280/ria.380231>
- [17] A. Imak, A. Celebi, K. Siddique, M. Turkoglu, A. Sengur and I. Salam, "Dental Caries Detection Using Score-Based Multi-Input Deep Convolutional Neural Network," in *IEEE Access*, vol. 10, pp. 18320–18329, 2022, doi: 10.1109/ACCESS.2022.3150358.
- [18] P. Singh and P. Sehgal, "Automated caries detection based on radon transformation and DCT," in *Proc. 8th Int. Conf. Comput. Commun. Netw. Technol. (ICCCNT)*, Jul. 2017, pp. 1–6, doi: 10.1109/ICCCNT.2017.8204030.
- [19] Rasool Esmailyfard, Haniyeh Bonyadifard, and M. Paknahad, "Dental Caries Detection and Classification in CBCT Images Using Deep Learning," *International Dental Journal*, Nov. 2023, doi: <https://doi.org/10.1016/j.identj.2023.10.003>.
- [20] K. Clark et al., "The Cancer Imaging Archive (TCIA): Maintaining and Operating a Public Information Repository," *Journal of Digital Imaging*, vol. 26, no. 6, pp. 1045–1057, Jul. 2013, doi: <https://doi.org/10.1007/s10278-013-9622-7>.